# AGENT BASED SEMIOLOGY: Simulating Contemporary Office Occupation Patterns with Simplified Social Models

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**Abstract:** Knowledge economy has become an increasingly important factor in recent years. Office environments have changed accordingly, and contemporary office space layouts have become more complex, as their qualities rely on their capacity to enhance the continuous transfer of knowledge and information rather than the exchange of work or goods. As the performance of these types of spaces becomes more difficult to assess, new methods need to be developed.

The research methodology described in this paper aims to predict the complex emerging spatial occupation patterns in contemporary office environments. Its ambition is to develop a novel method of architectural design that generates spatial environments with high social performativity. Embedded in the conceptual framework of agent-based simulation, this research does not foreground the configuration of space itself (like other tools such as space syntax) but rather focuses on devising behavioral rules of social interaction for a set of active agents within the space in question, with the goal to develop a population of agents that is sophisticated enough to allow for the emergence of an abstract, yet plausibly life-like collective event scenario, within an office space that features typical elements of interaction such as tables, desks and coffee bars. Behavioral patterns are driven by a carefully constructed simplified social model that differentiates agents according to their "social attractiveness" and their "social alignment", which govern the rules of interaction with other agents and objects in space. Results show that all simulations exhibit an overall life-like behavior when run and observed. Agents show differentiated behavior towards other agents and frame dependency to the varying distribution of objects in their space. Different space layouts result in differentiated spatial occupation patterns. While the overall number of interactions remains stable across all scenarios, the numbers for interactions with objects differ considerably depending on their location in space, indicating that different object formations within the same space influence the individual number of interactions and therefore render a space more or less performative.

**Keywords:** Agent-based semiology, work and office environments, contemporary spatial occupation patterns, digital design, social performance simulation, human space design

## INTRODUCTION

The built environment orders all social processes through semiological connotations as much as through physical boundaries. In this way, it guides and orients socialized agents, who need to understand and navigate their environment, via the comprehensibility of its visual representation to the same extent to which it channels physical bodies through its space. The "performance" of space, therefore, depends on its configuration, as well as on its capacity to appropriately frame its users' communications in context-sensitive ways.

Measuring and improving the performativity of office space and the workflow within it has been a topic of constant research since the second half of the 19th century, when Frederick W. Taylor began to develop his theory of scientific management. Since then, the nature of work and its underlying concepts have evolved considerably. Spatial layouts have become more diversified and interwoven and, as a consequence, the tools and methods of space analysis and evaluation have changed and matured too.

Soon after the traditional Taylorist office space layouts with their linear logic of mono-directional workflow had proven to be inadequate for the increasingly complex patterns of work that had emerged over time, designers started to develop innovative design strategies, such as the German Quickborner team's Bürolandschaft concept, whose office configurations were directly derived from the matrices and diagrams used to analyze the relations between different groups of co-workers within an office organization.

Although the concept still followed a strictly linear understanding of spatial distribution and workers' interaction, it offered two key innovations for the further development of office space design: for one, rather than content, it focused on patterns of communication, in order to use the flow of information as a generative tool. At the same time, it put an end to long-held spatial hierarchies, thus promoting informal face-to-face interaction, which was considered crucial in a cybernetic organizational model (Kockelkorn 2008).

In work environments that depend on a mostly linear transfer of work and goods, rather on the multi-directional exchange of information and knowledge, the success of a specific spatial configuration could be easily measured, for example by looking at the amount of paperwork done, or units assembled. Yet the performance of contemporary office space layouts that are designed to accommodate more complex social interaction patterns are much more difficult to assess.

## 1. TOOLS FOR ANALYSIS AND SIMULATION

### 1.1. SPACE SYNTAX AS AN ANALYTICAL TOOL

Of all the tools and techniques that have been established over the years to understand social spaces, space syntax remains the most popular and successful. Developed by Bill Hillier and Julienne Hanson, who—for the first time—proposed to look at the built environment, rather than as a mere aggregation of volumes and voids, as a social system that needs to be analyzed ". . . at the level of [a] system of spatial relations that constitute the building or settlement" (Hillier and Hanson 2003, 3) in order to understand societal effects in play. Initially developed to study and evaluate the varying patterns of public streets and squares in small hamlets, space syntax research was soon extended to investigate building interiors and other indoor social spaces. Space syntax today is widely used as a tool to understand the relationship between the morphological characteristics of office spaces, their occupational patterns, and the locations and frequency of the personal interactions of its users. Most commonly, this is achieved by applying space syntax's analytical concepts, such as integration, space, depth distance, and isovists, in order to quantify the configurational properties of a space. The results are then correlated to information about social interaction collected in the space or compiled from surveys or questionnaires taken by the employees working in that space or derived from network analysis (Peponis et al. 2007).

In his introduction to space syntax, Bafna summarizes that, "The primary object of analysis within space syntax research, then, is the configured space" which is ". . . redescribed in an abstracted format focusing on its topology". The premise at the base of this analytical procedure is ". . . that the sociologically relevant aspects of configured space can be captured at the level of topological description" (Bafna 2003, 19).

Recent studies, however, seem to indicate that, within the spatial constraints of a typically sized office space, social factors, such as an employee's position within an organization's hierarchy, her level of expertise or her membership with a specific group or department, outweigh spatial parameters, as ". . . managerial staff and experts are also attractors in the spatial system.", as Steen and Markhede observe (2010, 123). Therefore, in some instances, space syntax analysis produces inconclusive results, as the exact quantitative description of the space in question can no longer be matched to the changing patterns of interactions observed in the space.

Emerging spatial occupation patterns in contemporary office spaces, therefore, seem to increasingly rely on the interactions of the occupants ("agents") within their system and the social and semiological attributes that drive that behavior. As a consequence, the performance of a space can no longer be accurately measured by space syntax methodology alone, and the existing set of tools needs expansion to allow for the analysis of relational properties between a system's agents and their environment, in order to evaluate and refine spatial layouts.

### 1.2. AGENT-BASED SIMULATIONS

Within the last few years, knowledge economy has become an increasingly important factor in almost every developed country's service sector. In Western European countries, for example, knowledge economy at this point represents about a third of all economic activities (Eurostat 2013). As the economy's focus has shifted from the exchange of work or goods to constant human interaction and the transfer of information, various innovative types of knowledge work, with their respective mobility patterns, have emerged (Greene and Myerson 2011). Contemporary office space layouts accordingly become more multi-functional and interwoven, as their quality hinges on their capacity to facilitate formal and informal exchange of information between actors in complex and ever-changing configurations.

It is therefore the working hypothesis of this research, that in today's dynamic environments, spatial occupation patterns are no longer static or linear in nature, but start to show unpredictable and emergent configurations, which can be understood as the result of a multitude of (comparatively simple) interactions of the users of the environment in question, which gradually add up to the complex state of an emerging system. The results of such a bottom-up process can no longer be predicted by looking at spatial configurations but need to be understood by investigating the relationships between the actors within the space.

They can, therefore, be simulated using agent-based modeling (ABM), which in its most concise definition is "a computational method that enables a researcher [to] experiment with models composed of agents that interact within an environment" (Gilbert 2008, 2).

Craig Reynolds' computer simulation "Boids" (Reynolds 1987), in which he successfully reproduced the flocking behavior of birds in 1987, is generally considered the first agent-based simulation. Since then, the field of application for agent-based models has diversified and they are widely used for simulations in diverse fields, from biology to social sciences, mapping the processes that we assume to exist in a real social environment (Macy and Willner 2002).

However, architecture has only recently discovered them for the simulation of crowds in space. Similar to a flock of birds, human crowds show non-linear behavior, caused by the recurring iteration and superimposition of the interactions of their constituent components, which add up to the complex overall state of the system. They constitute emergent systems that can be studied and understood using agent-based modeling.

While plenty of commercial software programs offer readily available tools for crowd simulation, more complex life process simulations still require some scripting knowledge and the use of more specialized programs. For this research I will use NetLogo as an agent-based modeling and scripting language. NetLogo is a program designed for agent-based simulations, with built-in processes that are already designed to solve typical agent-based simulation scripting problems. It is open source software and caters to an academic environment. It is therefore easily accessible and draws from a large and active user community as ". . . there are a large number of agent-based models written in NetLogo in a wide variety of domains" (Wilensky and Rand 2015, xiv). As it is purely code based, it is fast, scalable and data extraction is easy. However, NetLogo's representational capacities are basic and visual output is limited to simple 2.5D graphic representation.

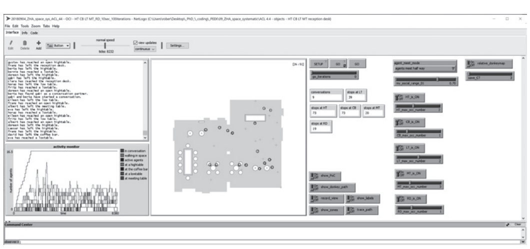


Figure 1: The NetLogo interface for the simulation. From left to right column: data readout windows, graphic representation of the simulation space, control panel. (Author, 2018)

## 2. RESEARCH METHODOLOGY

### 2.1. SIMULATION SETUP

In general, all agent-based simulation share the same set of characteristic features: ontological correspondence, a representation of the environment in question, a set of heterogeneous agents, and agent interactions based on bounded rationality (Fagiolo, Windrum, and Moneta 2006).

In this simulation, as an experimental setup, I use the layout of a contemporary office environment, which is modeled after an existing office in London. The research focuses on the office space's breakout space, which can be considered its most informal area, where face-to-face interaction can easily occur. Within the space, various typical office furniture elements are located; that foster unscheduled and spontaneous communicative encounters, but also allow for organized variously sized meetings and conferences in different constellations.

The space will be populated by sixteen agents, who enter and leave the space through one of the three available thresholds and navigate the space in order to interact with each other and the furniture elements at their disposal.

### 2.2. DEVELOPING A SIMPLIFIED SOCIAL MODEL

In office space research, the correlation between spatial proximity and the rate of face-to-face communication is well researched. Personal interactions, for example, decrease exponentially as the distance between a space's population increases, a relation whose graph is known as the Allen Curve (Allen 1984). However, more recent space syntax based research suggests that this discovery is accurate only for largely static office settings, whereas in more dynamic office environments, where a lot of circulation occurs, there is a strong correlation between interaction frequency and the intervisibility of the workers in the space (Markhede and Koch 2007).

Taking this into account, the research focuses on developing and refining agent-based simulations, in which the agents' behavioral rules and scripts are prompted not so much by distance or the position of the agent in relation to the space around him, but mainly by the social interaction with other agents and specific spatial or environmental features. The aim is to develop a population of agents with individual behavioral rules that are sophisticated enough to allow for the emergence of a simplified, yet plausibly life-like collective event scenario. For this, any agent-based simulation needs to include two key features of process modelling, agent differentiation and architectural frame dependency, allowing it to "move from the current evacuation and traffic-engineering crowds to architectural and semiological crowd, as the basis for generalized life-process simulation" (Schumacher 2016, 112).

Agents need to be differentiated by their position, status, group membership or importance within the social network, resulting in behavioral differences as they interact with each other. Agents also need to show architectural frame dependency, allowing for varying behavioral patterns depending on their location within a space and its architectural qualities.

This research aims to map complex real-life social interactions to a simplified social model for its agents, weighing the multiple variables in play in order to make them operational in a simulation.

### 2.3. SIMPLIFICATION AND BOUNDED RATIONALITY

Almost all social science research is conducted by devising simplified representations of social phenomena. In agent-based modeling, agents need to be understood as computational processes, which are coded in order to model human capabilities in a highly simplified way. Computational agents are, therefore, always limited in their cognitive abilities; they are modeled to act with bounded rationality.

The concept of bounded rationality was first introduced by Herbert A. Simon (1957), who suggested that, rather than assuming that an individual's choices are perfectly rational, one should understand the rationality within any decision-making process to be limited, as the amount of information is limited; human minds only have a limited capacity of evaluation and there is only a limited amount of time to make a decision.

It is safe to assume that the complex and changing occupational patterns in contemporary office spaces are influenced by a multitude of different non-spatial factors, albeit to a different degree. These factors might be differentiated into quantitative factors, such as fellow agents, office objects or architectural features, and qualitative factors, such as light, temperature, cultural context, or work atmosphere. While quantitative factors will trigger certain interaction patterns, qualitative factors might influence the probability, intensity, duration or sequence of these patterns.

In this research, the agents' behavioral abilities are developed gradually, starting from quite simple rules of interaction. The challenge is therefore ". . . not to limit the rationality of agents, but to extend their intelligence to the point where they could make decisions of the same sophistication as is commonplace among people" (Gilbert 2008, 16). The simulation needs to be set up in a way that allows for the implementation of the agents' capacities in different stages, first focusing on the ones that are considered most important.

### 2.4. BASIC PARAMETERS OF SOCIAL INTERACTION

The research, therefore, investigates the basics of spontaneous face-to-face conversation first, and focuses on two essential questions: "Who interacts with whom?" and "How long does this interaction last?". The dynamics of the interactions taking place between agents within the simulation space is described by operationalizing two values that are conceived to be numerical representations of the complex social parameters that drive these relations.

The selection process for possible conversation partners is governed by a variable called "social attractiveness" that quantifies the social differentiation between the agents (such as social status, hierarchy, knowledge or information or physical attractiveness) and is defined by a value from zero to one. In general, agents will always try to interact with the agent with the highest social attractiveness present at any time in the simulation. However, some constraints apply. Agents will always operate within two different ranges, confining their respective interaction radii. First there is a "physical range" limiting the set of available agents to those within a pre-set spatial proximity defined by distance and visibility. Then, more importantly, we introduce another parameter called "social range", which sets the maximum difference in social attractiveness that still allows for social interaction.

While the physical range, in a simplified way, defines the spatial limits of successful personal communication, the social range, which is developed for this set of simulations, starts to describe the relationship between patterns of communication and the social environment they are embedded in. It defines the permeability of the hierarchical structures of a specific corporate (or societal) culture, also drawing on the observation that the constellations, frequency and duration of conversations will be considerably different in culture groups with divergent concepts of hierarchy. It reflects observable restrictions from real-life social scenarios, where big differences in status or hierarchy usually preclude social interaction. The social range consequently defines a sub-set of agents with whom a specific agent is socially allowed to engage. Furthermore, agents who are already engaged in some sort of interactivity are considered unavailable for interaction.

In this simulation, agents will therefore always look for and try to interact with an available agent with the highest social attractiveness within its social and physical range.

The duration of any social interaction is determined by calculating differences of value of a variable called "social alignment". It represents an agent's personal properties (such as personality, profession, expertise, fields of interest and knowledge, or acquaintances) as a vector with a directional value between 0 and 360 degrees. The more the vectors of two interacting agents align (i.e., the more they have in common), the longer their interaction will last.

It should be added, that at this point of the research, all values that determine the agents' behavioral properties are assigned randomly as placeholders that can later be substituted by more viable social data, which can, for example, be extracted from social network analysis.

Systematic modulations of the values for the agents' social and physical range will generate a number of distinct spatial occupation patterns. For example, setting a high value for physical range and a low value for social range will result in longer travel distances and fewer social interactions.  Inverting these values on the other hand will lead to a high number of social interactions within a small spatial field.

It is reasonable to assume that in clearly confined office spaces not only fellow agents, but also inanimate objects will influence the spatial occupation patterns of its users. Steen and Markhede (2010) also notice this, stressing the equal importance of "hard artefacts" and "office workers" in the analysis of spatial and social configurations in offices (123). This is especially true for common areas, such as lobbies, break rooms, or communication spaces, where one would expect to find office elements such as coffee bars, reception desks, high tables, low tables, and meeting tables in various configurations~~,~~ that cater for common, yet always temporary, needs and desires of their users, triggering frame dependent behavior.

For the scope of this set of simulations, the simplified social model developed for the agents is equally applied to the office objects in it. Values are assigned as placeholders for characteristics that might influence the attractiveness of a specific element, like the type of an object (such as coffee bar or high table) or its location within the office space (for example next to the entrance, in the middle of the room, or in a remote corner). Coffee bars almost always have a rather high level of social attractiveness. Similar to the rules applied to person-to-person interaction, a combination of agents and objects will temporarily acquire new combined values for social attractiveness and social alignment for as long as they interact with each other. For example, a remote table's attractiveness will increase with managerial staff standing next to it, whereas agents with low social attractiveness populating the coffee bar will decrease this combination's overall value, thus making it approachable for a different subset of agents, as any agent will always attempt to interact with the set of entities that has the highest attractiveness within its social and physical range.

Again, every modification of the physical and social ranges of agents and objects will create distinctively different patterns of spatial occupation and interaction. Setting high ranges for agents and low ranges for objects will, for example, lead to a high rate of free-floating agent-to-agent conversations and little interaction with the objects in the space. Setting high ranges for objects and low ranges for agents on the other hand will result in frequent agent-object interaction and almost eliminate personal conversations from the simulation.

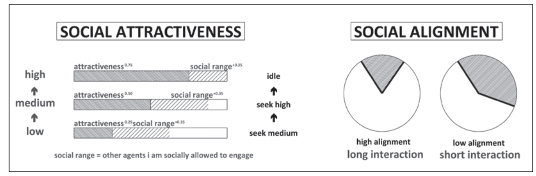



Figure 2: Social Attractiveness and Social Alignment are defined as the key variables that drive the agents' behavioral patterns in a simplified social model of interaction. (Agent-based Parametric Semiology Research Group–Josip Bajcer, 2017)

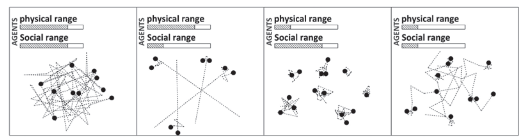



Figure 3: Different values for an agent's social and physical range will generate a wide variety of different spatial occupation patterns. (Agent-based Parametric Semiology Research Group–Josip Bajcer, 2017)

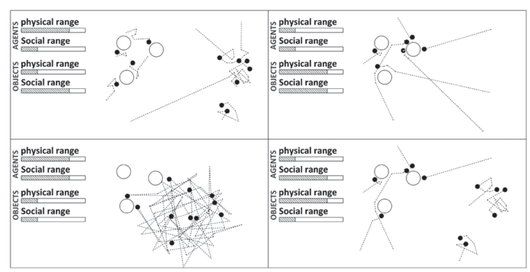



Figure 4: Different values for social and physical ranges of agents and objects will generate a wide variety of different spatial occupation patterns. (Agent-based Parametric Semiology Research Group–Josip Bajcer, 2017)

## 2.5. SETTING UP A RESEARCH MATRIX

While the random walk, a sequence of randomly directed individual steps that are strictly independent of one another on a two-dimensional plane is often described as the most simple concept of movement in an agent-based model (O'Sullivan and Perry 2013), the starting point for this simulation is a rudimentary agent model with agents wandering around unaware of themselves and each other, walking without interaction or collision avoidance towards randomly assigned targets within a given range. Subsequently, the simulation's complexity is increased step by step to develop a generic agent model with fundamental navigational properties.

The simple social model described above is then implemented on top of this successfully tested generic agent model, which at this point already contains scripted processes for spatial navigation, simple fields of vision, collision avoidance, object and agent recognition, and detection of entrance and exit areas.

In subsequent steps, the agents' capabilities are systematically extended to allow for patterns of interaction with a number of common office furniture elements taken from the office layout developed earlier, such as high tables, low tables, a meeting table, a reception desk, and a coffee bar.

As in other strands of digital design research, repeatedly testing and refining the scripted processes becomes important for a systematic approach to problem solving, once a basic logic has been established (Neumayr and Budig 2009). For improved systematic comparison, simulations are therefore organized in a 2-dimensional matrix. The vertical axis holds the levels of agent complexity (agent capacity level–ACL), starting with the simplest possible agent as described above (ACL 1.0) and ending with—at this point— behavioral rules for the interaction with five different furniture elements (ACL 4.4).

The result is a cummulative buildup of potential agent capacities that allows for direct comparison of the different levels of complexity and, as a consequence, offers insight into the relevance of specific agent capacities in relation to the agents' simulation environment.

On the horizontal axis, four parallel office scenarios are simulated for each agent capacity level, in order to produce a reliable set of data. While the number and type of office furniture and interaction objects, as well as the number of entry and exit points, stay the same for each of the scenarios, their locations in the space varied systematically. In each simulation, the maximum number of agents (sixteen) and the simulation time of thirty minutes remain unchanged. During simulation runtime, all relevant information, such as every agent's position (in one second intervals), their speed, direction, and path, but also the time, location, and duration of their interactions and encounters are recorded and stored in a data base for later analysis and comparison. For each scenario, the simulation is run 100 times in order to check for consistence, minimum and maximum values, average, standard deviation, and outliers. The data collected is first used to create a number of graphs and visual quantifiers, such as heat maps (showing the occupation patterns over time), location maps, and trail maps tracking the movement of each individual agent.

### 3. SIMULATION RESULTS AND FINDINGS

All agent-based office space simulations, that are based on the simplified social model are assessed on different levels.

To begin, in order to check for plausibility, all agent behavior is evaluated according to their susceptibility to agent differentiation and frame dependency. In a first step this is done by analyzing a simulation's visual output during runtime. During simulations, agents show differentiated behavioral patterns towards other agents holding varying social properties, as well as towards objects of interest distributed in the space. Observations show that the selection process for social interaction and spatial occupation follows an intricate set of instructions and does not result from simple rules, such as distance or visibility.

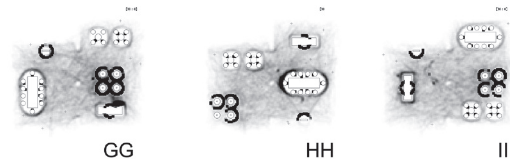


Figure 5: Heatmaps of the simulation of three different office space layouts (GG, HH, II), showing the different patterns of agent occupation resulting from the varying location of objects. (Author 2019)

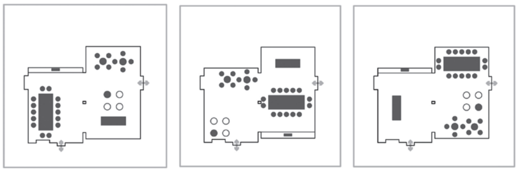
This observation is confirmed by comparing the heat maps of different simulation setups. Heat maps show the occupation patterns of all agents accumulated over time and superimposed in one image. As the objects' positions in the space vary across different simulation setups, the agents' behavior (and with it their locations in the space) shifts and adapt accordingly.

In terms of consistency and frame dependency simulation, results are assessed by analyzing the agent data recorded during each simulation. Here, the frequencies of the various agent-to-agent and agent-to-object interactions were investigated.

Looking at a series of simulations in an identical and closely confined simulation space, with a fixed number of active agents and a constant number of interaction objects, whose positions are strategically modified to be different in each simulation, one would expect to find a similar, yet not identical, total number of interactions, but at the same time diverging values for the agents' interactions with the objects in the space.

The numbers taken from the three simulations in ACL 4.4 confirm this expectation: While the total number of interactions for all sixteen agents lies between 204 and 208 and therefore does not change significantly, the values for agent-to-agent conversation (free conversations) and various agent-to-object interactions vary considerably from simulation to simulation. The number of free conversations ranges from 13 to 43, values for high table interaction ranges from 61 to 95, for low tables from 31 to 41, for the reception desk from 11 to 16, and for the meeting table from 27 to 47. The interaction value for the coffee bar, which is always located next to a wall, shows the smallest variance (from 15 to 17).

The information from the first three simulation scenarios in every ACL are also used to train a statistics-based prediction algorithm to forecast the spatial occupation pattern for the fourth scenario. The



| GG # of conversations | | HH # of conversations | | II # of conversations | |
|---|---|---|---|---|---|
| free | 13,08 | free | 24,68 | free | 43,16 |
| @ high table | 95,24 | @ high table | 61,16 | @ high table | 71,76 |
| @ low table | 31,42 | @ low table | 41,02 | @ low table | 31,66 |
| @ coffe bar | 15,14 | @ coffe bar | 15,36 | @ coffe bar | 17,26 |
| @ reception | 10,90 | @ reception | 14,44 | @ reception | 16,10 |
| @ meeting table | 42,20 | @ meeting table | 47,12 | @ meeting table | 26,52 |

total # of conversation ranges between 203 - 209 (not significant)

Figure 6: Table of interaction frequencies for three different scenarios (GG, HH, II). Green and Red indicate maximum and minimum values for the interaction with specific objects within the entire set of simulations. (Author 2019)

algorithm's results are then compared to the results of the agent-based simulation of that scenario condition for consistency. Details about this related strand of research were recently published in a separate research paper (Fuchs and Neumayr 2020).

## DISCUSSION AND OUTLOOK

As of now, the simulations developed for this strand of research show an overall life-like behavior when run and observed. Agents exhibit differentiated behavior towards other agents and frame dependency to the changing object distribution in the simulation space. The cumulative behavior over time results in differentiated spatial occupation patterns throughout different scenarios.

The overall number of interactions remains stable across all scenarios, whereas the numbers for individual interactions vary significantly from one simulation to another, indicating that different object formations within one and the same space do indeed influence the number of interactions, and—as a consequence—render a space more or less performative.

Based on these findings, further explorations are necessary, with the aim to discover more reliable correlations between the objects' locations and the resulting interaction numbers.

At this time, the question of the realism of these simulations is difficult to answer. In this respect, more experimental investigation will be necessary, as well as calibration of the simulation results with observations, and sensor data collected in the office space that is simulated here.

I will also argue that, in order to comparatively evaluate and select the most suited design alternative from within a design space, no absolutely accurate performance measurements are necessary. The empirical notion that a spatial organization's relative advantages in performativity can be accurately described, even if absolute performance measures might be imprecise, appears as a valid first step, warranting further investigations into this design methodology.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